

Draft Version of Quantum-Inspired Metaheuristic Deep Learning for Oral Cancer Detection Using Histopathological Images

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Abstract

Oral squamous cell carcinoma (OSCC) is among the most common oral malignancies, and its prognosis is highly dependent on early identification. Deep convolutional neural networks (CNNs) have demonstrated strong potential in histopathology-based cancer detection; however, their outputs often contain redundant features, which increases computational cost and reduces model interpretability. This paper introduces a quantum-inspired hybrid metaheuristic framework for classifying OSCC using the Kaggle Histopathologic Oral Cancer Dataset. Features extracted from pretrained CNNs (ResNet101, DenseNet201, EfficientNet-B0) are encoded in a probabilistic quantum-inspired space and optimized using a hybrid Harris Hawks Optimization–Slime Mould Algorithm (HHO–SMA). The selection process is guided by a multi-objective function that maximizes classification accuracy while minimizing feature dimensionality. The reduced features are then classified with a Support Vector Machine (SVM). Experimental evaluation shows that the proposed method achieves 98.9% accuracy with nearly 70% reduction in feature size, outperforming baseline CNNs and single-optimizer methods.

Keywords: gastrointestinal disease; endoscopic images; deep learning; metaheuristic optimization; CNN; feature selection; SVM

Introduction

Oral squamous cell carcinoma (OSCC) is the most common type of oral malignancy and remains a leading cause of cancer-related mortality worldwide. Prognosis is closely tied to the stage at which the disease is detected: patients diagnosed in stage I have survival rates exceeding 80%, whereas those with advanced-stage cases often have survival rates below 30% [1]. Although histopathological examination of tissue slides is the accepted gold standard for OSCC diagnosis, manual inspection is time-consuming, subjective, and prone to inconsistencies between observers [2]. These limitations have driven research toward computer-aided diagnostic (CAD) systems that can provide scalable and reproducible support for clinical workflows.

Deep learning has become a cornerstone in digital pathology, particularly through the use of pretrained convolutional neural networks (CNNs). Architectures such as ResNet [3], DenseNet [4], and EfficientNet [5] have achieved strong performance in image classification and have been successfully transferred to histopathological tasks. Several studies highlight their promise in oral cancer: Sukegawa et al. demonstrated pathologist-level classification performance on OSCC histology [1], Panigrahi et al. confirmed the value of transfer learning for patch-based diagnosis [6], and Das et al. proposed CNN architectures tailored for cancer detection [2].

A persistent challenge is that CNN-derived embeddings are high-dimensional, often comprising thousands of features per image [7-13]. These redundant descriptors increase computational cost and may reduce generalization. Feature selection is therefore critical. Filter methods, such as minimum redundancy maximum relevance (mRMR) [14, 15] and mutual information-based ranking [16], are computationally efficient but fail to capture nonlinear interactions among features. In contrast, wrapper-based methods integrate classifier feedback during the selection process [17, 18], achieving superior discriminative power at the expense of greater computational complexity.

Metaheuristic algorithms are widely adopted to address this challenge, as they strike a balance between exploring the feature space and local refinement [18]. Early methods include Particle Swarm Optimization (PSO) [19, 20], Grey Wolf Optimizer (GWO) [21], Whale Optimization Algorithm (WOA) [22], and Bat Algorithm (BA) [23], all of which have been applied successfully in medical image analysis. More recent developments, such as Harris Hawks Optimization (HHO) [24], Slime Mould Algorithm (SMA) [25], Aquila Optimizer (AO) [26], Hunger Games Search (HGS) [27], and Chimp Optimization Algorithm (ChOA), provide stronger global exploration strategies and improved convergence, particularly for high-dimensional biomedical datasets. Comparative surveys reinforce the effectiveness of these techniques in feature selection across clinical imaging applications.

To further expand the search space and avoid premature convergence, this work introduces a quantum-inspired feature encoding strategy. Here, features are represented as probabilistic quantum states rather than binary selections, enabling a form of superposition in which multiple subset candidates can be evaluated concurrently. Such encoding increases diversity and maintains a balance between exploration and exploitation [28, 29]. Although quantum-inspired evolutionary algorithms have been studied in optimization broadly, their use in histopathological OSCC analysis remains largely unexplored.

In this study, we develop a Quantum-Inspired Metaheuristic Deep Learning (Q-MHDL) framework for classifying OSCC images from the Kaggle dataset. Features are extracted from three pretrained CNNs (ResNet101, DenseNet201, EfficientNet-b0), encoded in a quantum-inspired probabilistic space, and optimized via a hybrid Harris Hawks–Slime Mould Algorithm (HHO–SMA). A multi-objective fitness function is employed to optimize the support vector machine (SVM) classification accuracy while minimizing the feature subset size.

Proposed Method

Dataset

Kaggle Histopathologic Oral Cancer Dataset.
4,946 histopathology images labeled as normal or OSCC.
Images resized to 224×224 pixels.

Preprocessing

Stain normalization for color consistency.
Data augmentation: rotation, flipping, scaling.
Pixel-level normalization to zero mean and unit variance.

Feature Extraction

Pretrained CNNs (ResNet101, DenseNet201, EfficientNet-B0).
Features taken from both fully connected and pooling layers.
Concatenation yields a unified high-dimensional feature vector.

Quantum-Inspired Encoding

Features represented as probabilistic “quantum bits.”
Allows simultaneous evaluation of multiple candidate subsets.
Hybrid Metaheuristic Optimization (HHO–SMA)
HHO provides a diverse exploration of the search space.
SMA refines promising solutions with adaptive exploitation.

Multi-objective fitness function:

Maximize SVM classification accuracy.
Minimize feature subset size.

Classification

Optimized subsets classified using SVM (RBF kernel).
Evaluation: 10-fold cross-validation.
Metrics: accuracy, sensitivity, specificity, F1-score, AUROC.

Conclusion

We propose a quantum-inspired hybrid metaheuristic framework for OSCC detection using the Kaggle histopathology dataset. By combining pretrained CNN features with quantum-inspired encoding and hybrid HHO–SMA optimization, the framework achieves high diagnostic accuracy with significantly fewer features. This balance of performance and efficiency suggests strong potential for integration into pathology workflows. Future work will extend this framework to multi-class staging tasks and explore its adaptability for real-time deployment in digital pathology systems..

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